Multi-robot Shaping of Deformable Objects based on Mechanical Simulation

GT SYSME day - Tarbes, September 30th, 2022

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- **Laurent Lequièvre**, Institut Pascal, CNRS
- Dr. **Paul Baksic**, iCube, Université de Strasbourg
- Dr. **Hadrien Courtecuisse**, iCube, Inria Grand Est
- Prof. **Thibaut Raharijaona**, LCFC, Université de Lorraine

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Robotix-Academy
Fonds européen de développement régional | Europäischer Fonds für regionale Entwicklung

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2. Contribution outline
3. Methods
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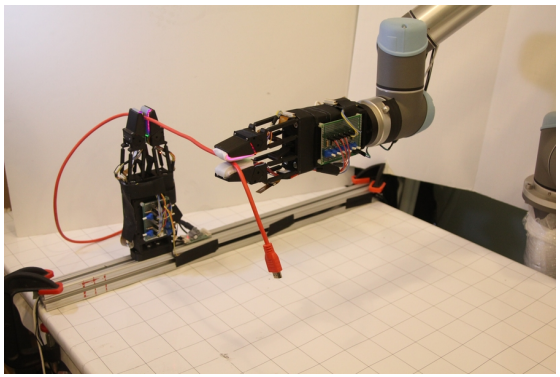
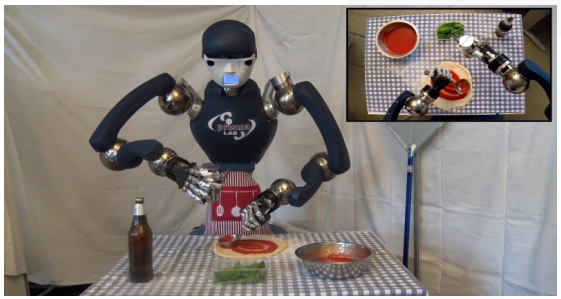
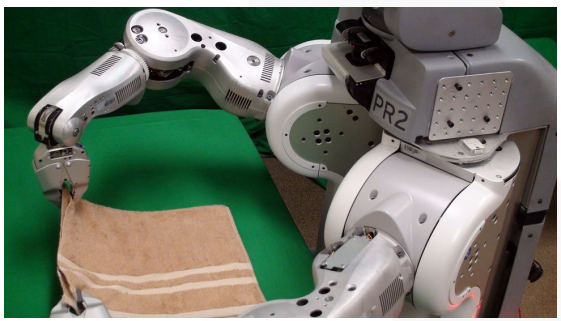
Context

Industry

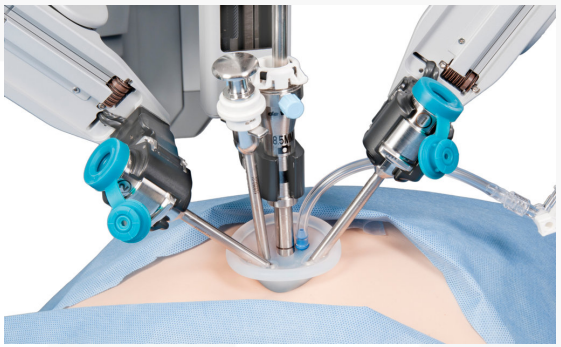


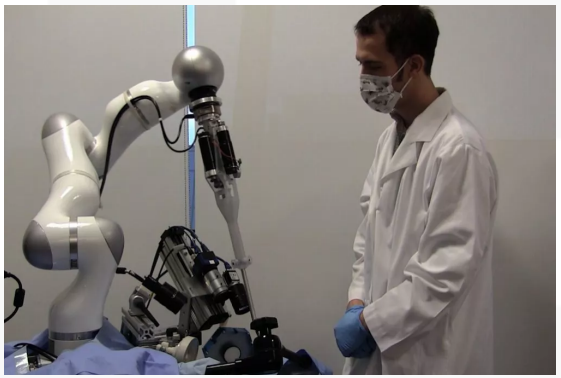
Household





Medical





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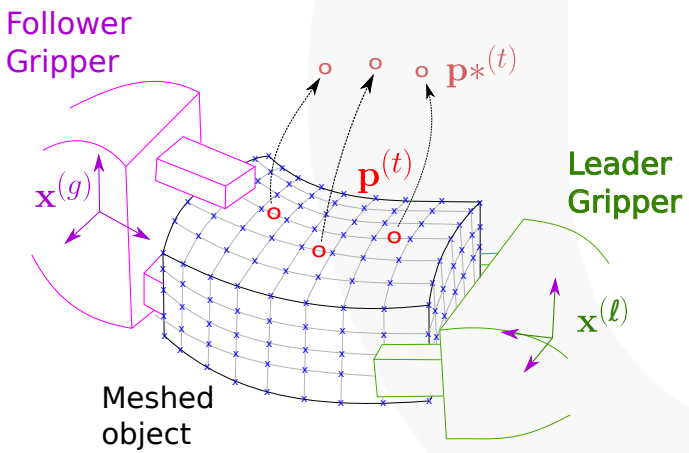

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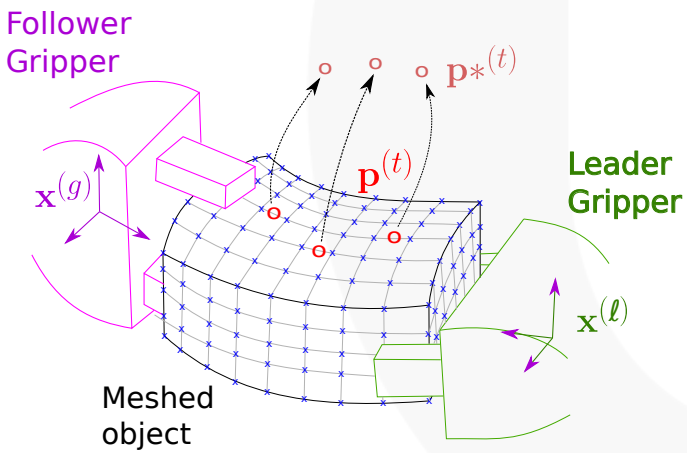
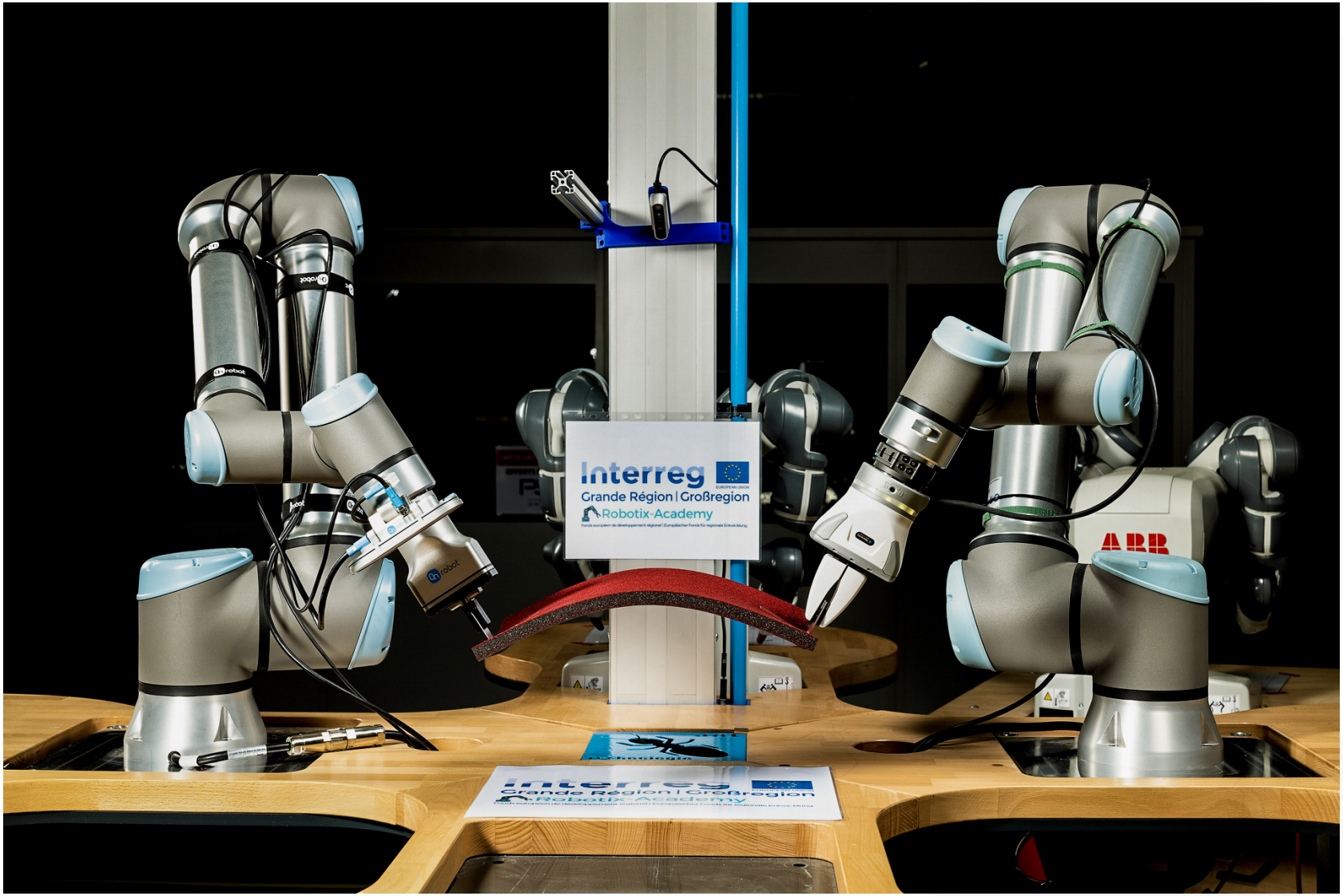


How to link $\mathbf{x}^{(g\ell)}$ and $\mathbf{p}^{(t)}$?

Manipulation example



Interaction Jacobian Matrix

The relation between $\mathbf{x}^{(g\ell)}$ and $\mathbf{p}^{(t)}$ is often linearized over time steps as:

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Estimating $\mathbf{J}_{inv}$ is of **crucial interest for shape control**
$\rightarrow$ Compute gripper motion to reach a given shape.

Literature overview

Desired shape formulation:

Jacobian $\mathbf{J}$ estimation:

[1][2][3] Zhu et al., RAS 142, 2021. Lagneau et al., RA-L 5(4), 2020. Laezza et al., ICRA 2021
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Desired shape formulation:

- Vision-based - $\mathbf{p}*^{(t)}$ are visual features, $p*_i^{(t)} = (u_i, v_i)$
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  Easily linked with camera calibration

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- Mechanical models:

Pseudo-physical models

- Diminishing rigidity[4]
- Position-based dynamics[5]
- As-rigid-as-possible[6]

Mechanical models

- Exact models (catenary)[7]
- Mass-spring-damper models[8]
- Finite element analysis[9]

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- Models may include external interactions

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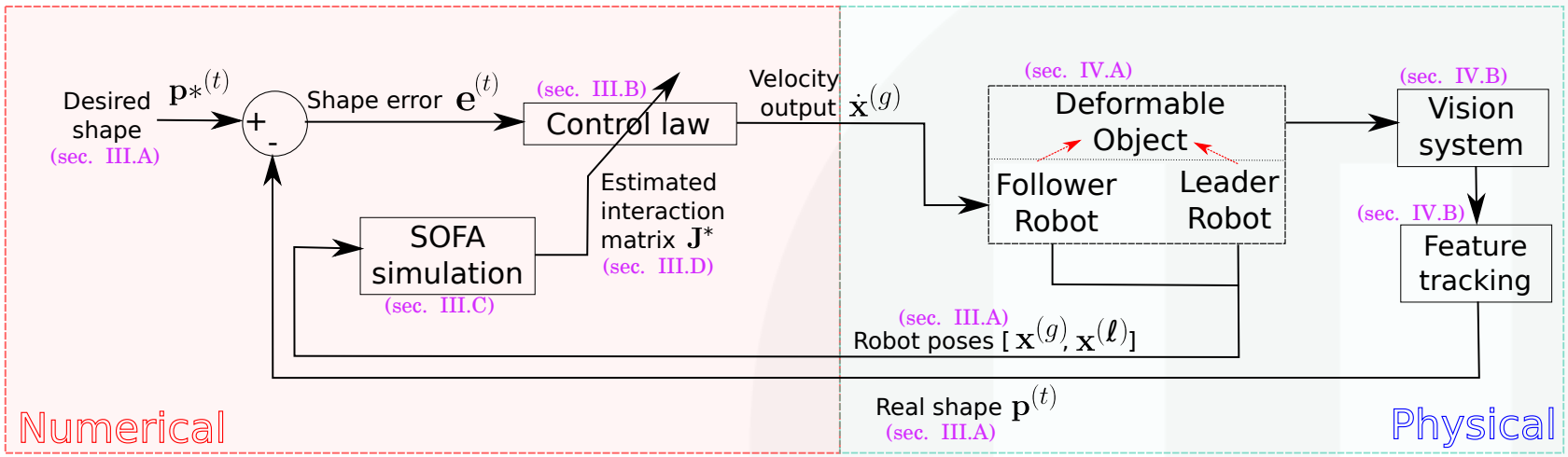
→ Merged in the proposed contribution.

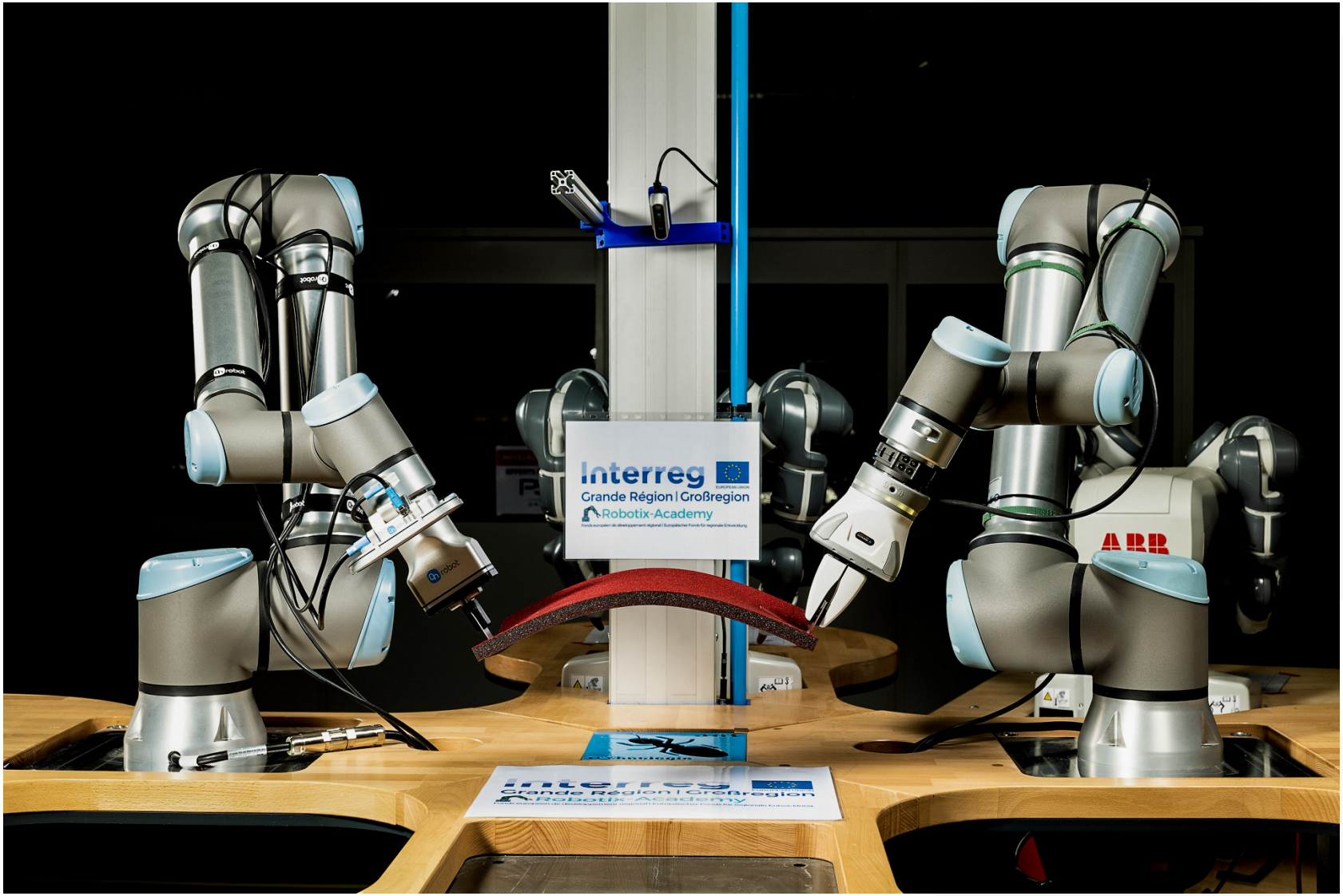
Contribution overview



Main elements:

- Proportional control law
- Visual feedback
- Finite element simulation
- Physical system : robots + deformable object

Experimental setup



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Definitions:

- $\mathbf{p}^{(t)}$ - perceived shape
- $\mathbf{e}^{(t)} = \mathbf{p}*^{(t)} - \mathbf{p}^{(t)}$ - shape error
- $\hat{\mathbf{J}}$ - estimated Interaction Jacobian Matrix

Proportional velocity control law such that $\mathbf{e}^{(t)} \rightarrow \mathbf{0}$:

$$\dot{\mathbf{x}}^{(g)} = \hat{\mathbf{J}}_{inv} \mathbf{G}_p \mathbf{e}^{(t)} \text{ with } \mathbf{G}_p > 0$$

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- Stability analysis wrt. $\mathbf{G}_p$
- Quality of $\mathbf{e}^{(t)}$ estimation
- Quality of $\hat{\mathbf{J}}$ estimation

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- Quality of $\hat{\mathbf{J}}$ estimation $\rightarrow$ **main concern!**

Jacobian estimation #1

Analytic method. Partition of the nodes of the mesh[10]:

- Grasped nodes g - in contact with the robot
- Target nodes t - defining the target shape to reach
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$$\mathbf{K}(\mathbf{u})\boldsymbol{\Delta}\mathbf{u} = \boldsymbol{\Delta}\mathbf{f} \quad \Rightarrow \quad \begin{aligned} \mathbf{K}_{gg}\boldsymbol{\Delta}\mathbf{u}_g + \mathbf{K}_{gt}\boldsymbol{\Delta}\mathbf{u}_t + \mathbf{K}_{gf}\boldsymbol{\Delta}\mathbf{u}_f &= \boldsymbol{\Delta}\mathbf{f}_g \\ \mathbf{K}_{tg}\boldsymbol{\Delta}\mathbf{u}_g + \mathbf{K}_{tt}\boldsymbol{\Delta}\mathbf{u}_t + \mathbf{K}_{tf}\boldsymbol{\Delta}\mathbf{u}_f &= \boldsymbol{\Delta}\mathbf{f}_t \\ \mathbf{K}_{fg}\boldsymbol{\Delta}\mathbf{u}_g + \mathbf{K}_{ft}\boldsymbol{\Delta}\mathbf{u}_t + \mathbf{K}_{ff}\boldsymbol{\Delta}\mathbf{u}_f &= \boldsymbol{\Delta}\mathbf{f}_f. \end{aligned}$$

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Assuming constant external efforts, it holds

$$\mathbf{J} = -(\mathbf{K}_{td} - \mathbf{K}_{tf}\mathbf{K}_{ff}^{-1}\mathbf{K}_{fd})^{+}(\mathbf{K}_{tt} - \mathbf{K}_{tf}\mathbf{K}_{ff}^{-1}\mathbf{K}_{ft})$$

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However, inverting $\mathbf{K}_{ff}$ becomes untractable for finely meshed objects.

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Jacobian estimation #2

Simulation method. Computation of the Jacobian using finite differences[11].

For each DOF j of the gripper, a small perturbation $\mathbf{\Delta}[:, j]$ is introduced:

$\mathbf{p}^{(t)} = \text{simulate}(\mathbf{x}^{(g)})$
for $j = 1$ to $\text{length}(\mathbf{x}^{(g)})$ **do**
  $\mathbf{x}_{\Delta}^{(g)} = \mathbf{x}^{(g)} + \mathbf{\Delta}[:, j]$
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  $\hat{\mathbf{J}}[:, j] = (\mathbf{p}_{\Delta}^{(t)} - \mathbf{p}^{(t)})/(\|\Delta[:, j]\|)$
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The $\text{simulate}()$ method must be run $\text{length}(\mathbf{x}^{(g)}) + 1 = 7$ times to estimate $\hat{\mathbf{J}}$.

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$\rightarrow$ Less "explosive" computation, but high efficiency is still needed!

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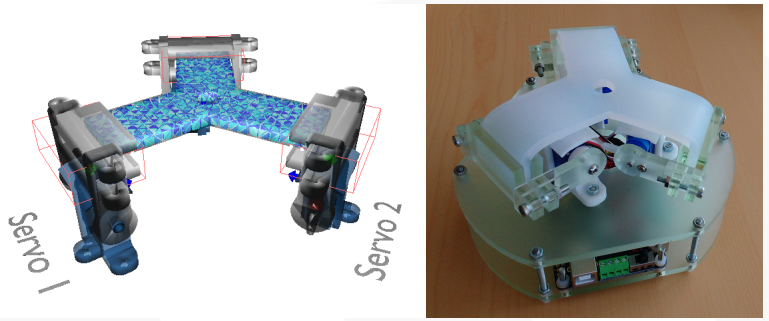
Time-efficient FE simulation

State of the art:

- Soft robot static analysis[12] and control[13]
- Surgical robotics[14]



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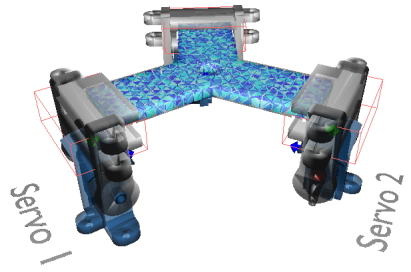

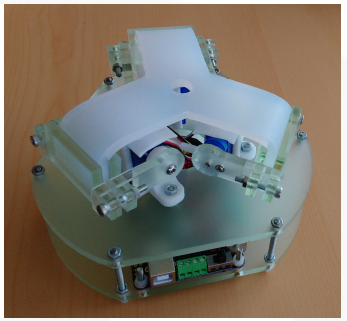

Software: Bullet, **SOFA framework**

- Parallelized GPU computing enabled
- Support from community (**Inria MIMESIS** and DEFROST teams)

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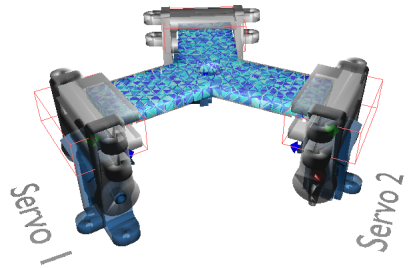

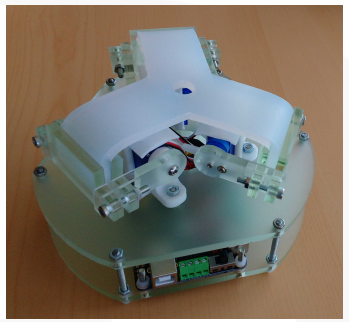

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Tricks for fast computation:[15]

- Parallel computing (LDL decomposition)
- System preconditioning
- Approximated inverse matrices

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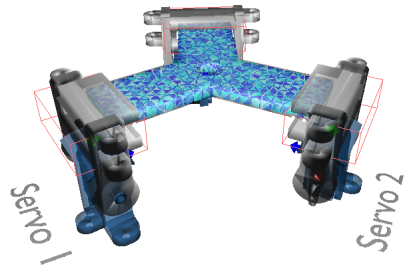

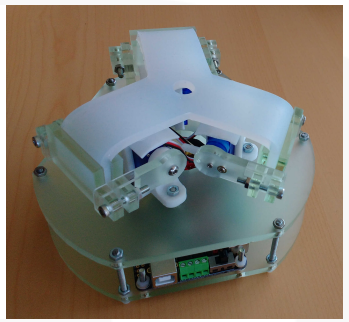

Software: Bullet, **SOFA framework**

- Parallelized GPU computing enabled
- Support from community (**Inria MIMESIS** and DEFROST teams)

Tricks for fast computation:[15]

- Parallel computing (LDL decomposition)
- System preconditioning
- Approximated inverse matrices

$\rightarrow$ Experimental assessment of $\hat{\mathbf{J}}$ computation frequency

[12] Koehler et al., RA-L 4(2), 2019
[13] Katzschmann et al., RoboSoft 2019
[14] Coevoet et al., RA-L 7(2), 2022
[15] Baksic et al., ICRA 2021

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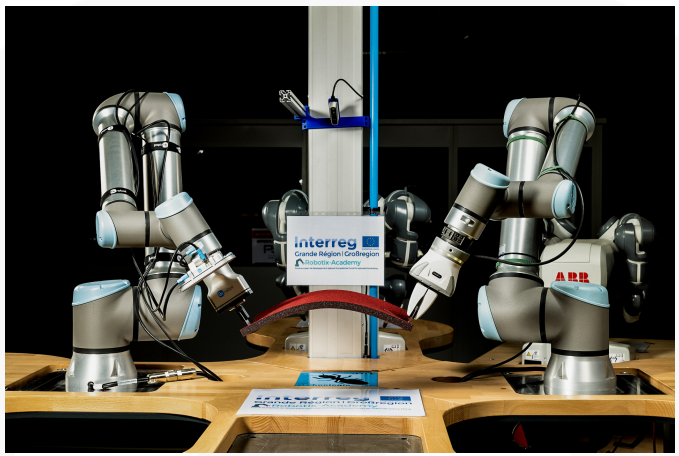

[16] https://github.com/UniversalRobots/Universal_Robots_ROS_Driver
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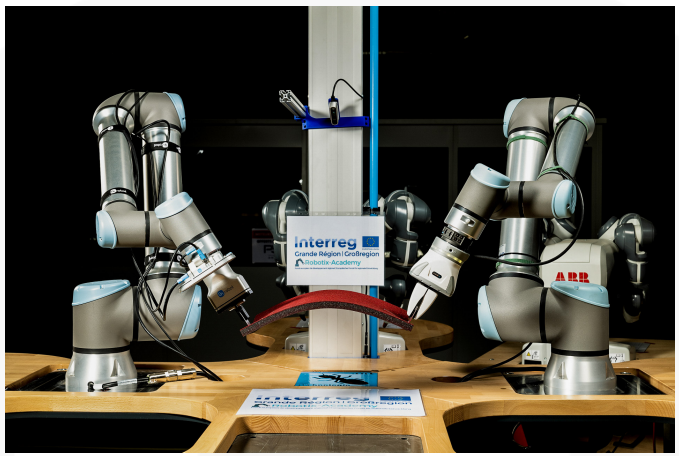
- Painted foam with adhesive markers
- Tensile testing: $E = 95$ kPa, $\nu = 0.45$.



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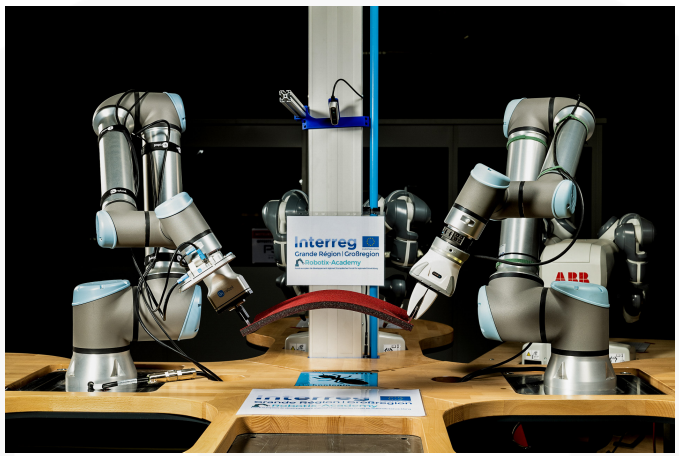

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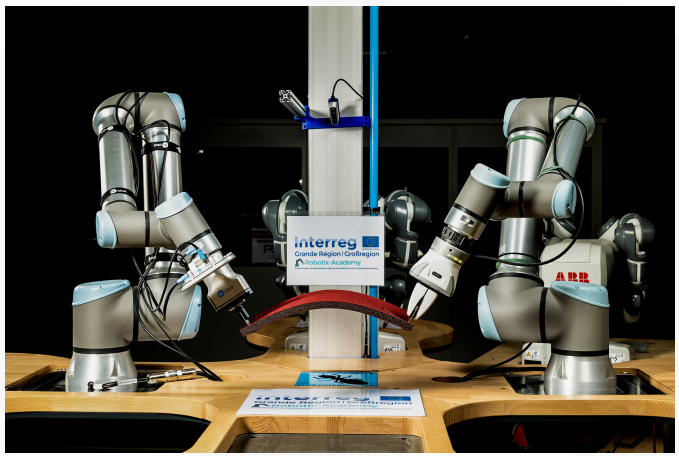

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SOFA simulation:

- Co-rotational modeling, linear elasticity, 1452 tetrahedra
- Python scripting[17] + custom libraries

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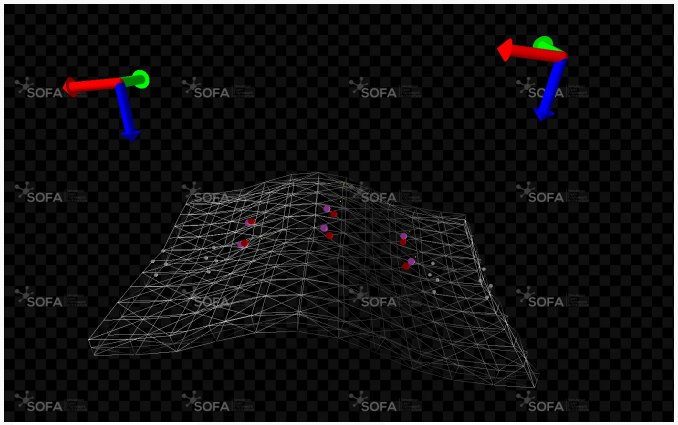
Setup assessment

Modeling errors:

- Coarse mesh, unrealistic deformation at grasping points
- Unmodeled viscosity
- Manual positioning at $t = 0$



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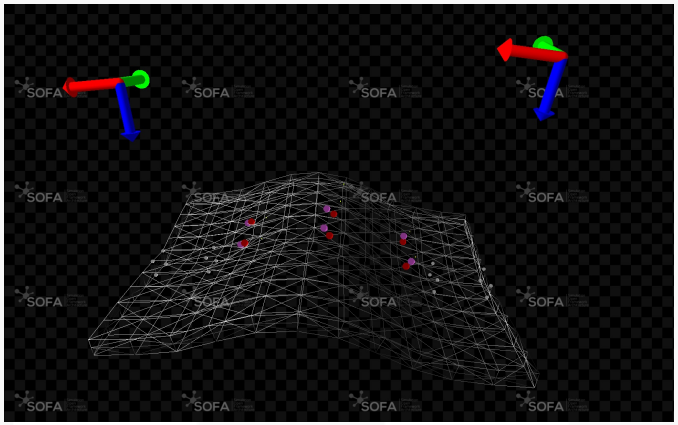
$\rightarrow$ looking for vision-based non-rigid registration



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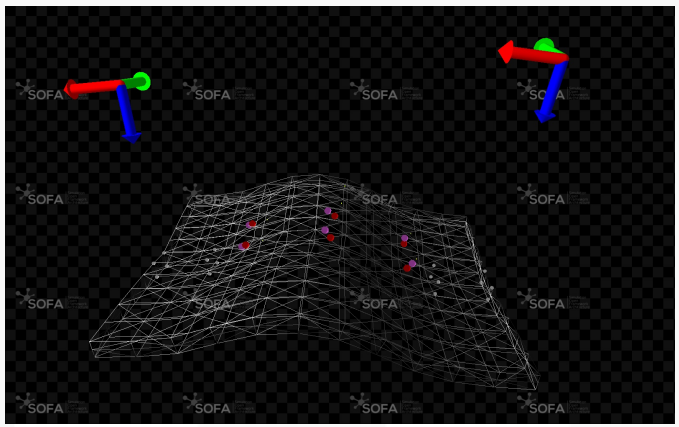

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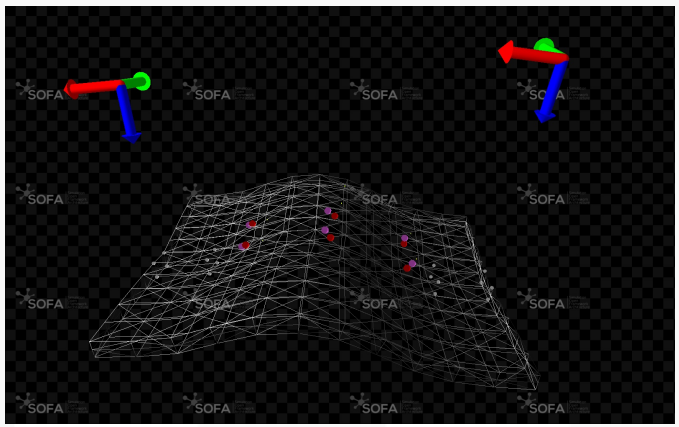

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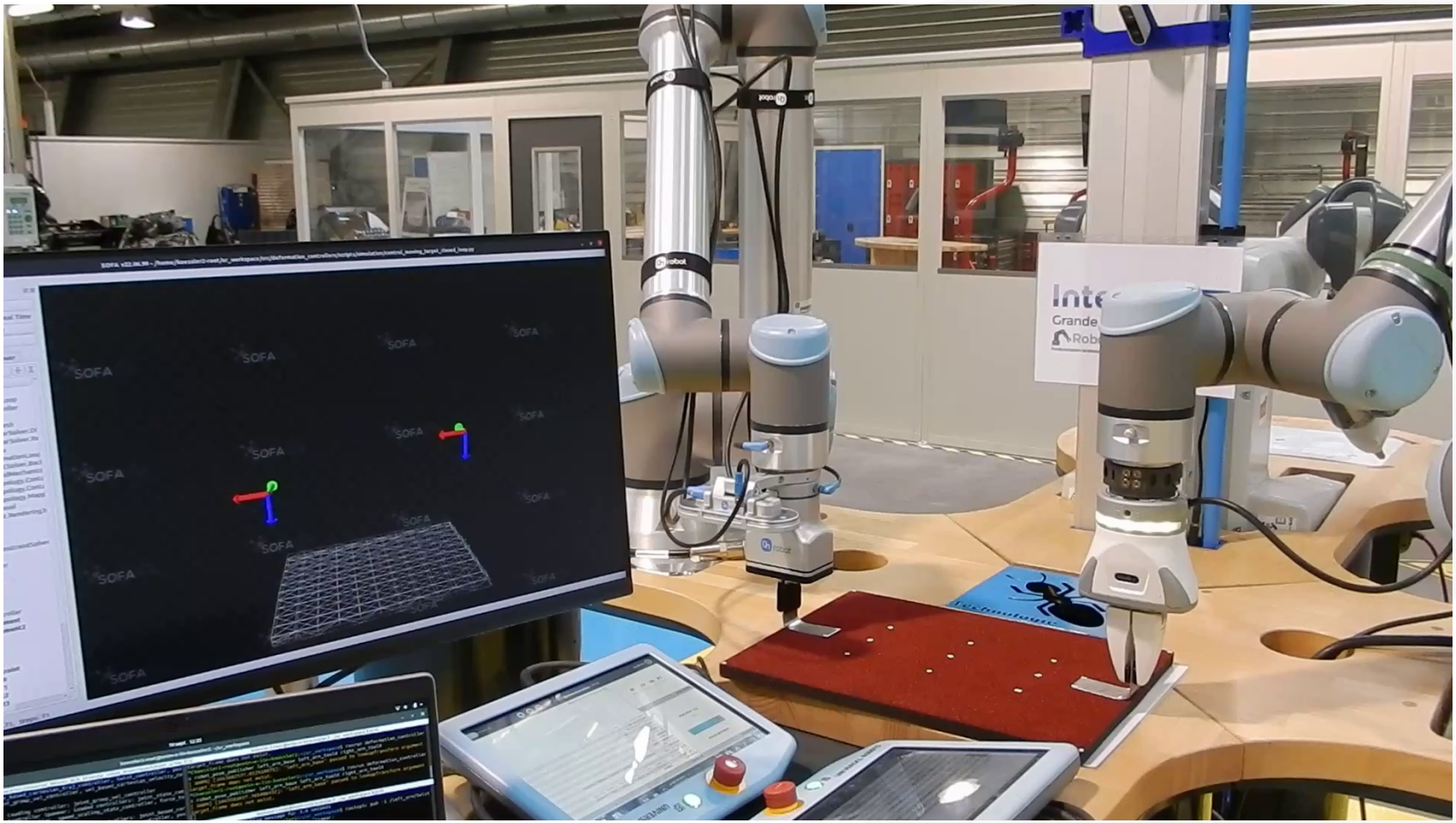
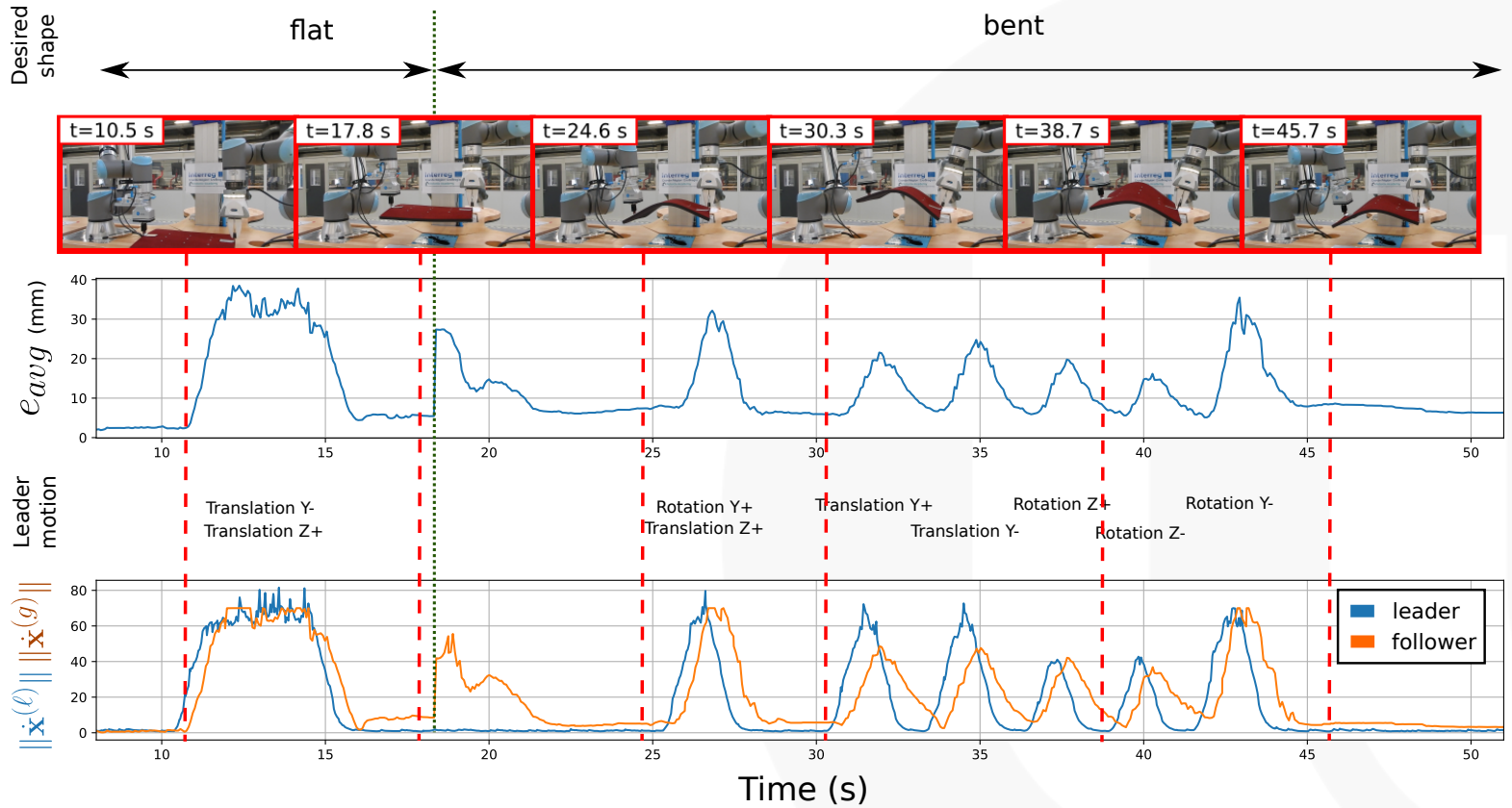
→ Shaping precision cannot be assessed finely
→ Need for a ground truth in the future

Online experiment - Shape recovery along trajectory

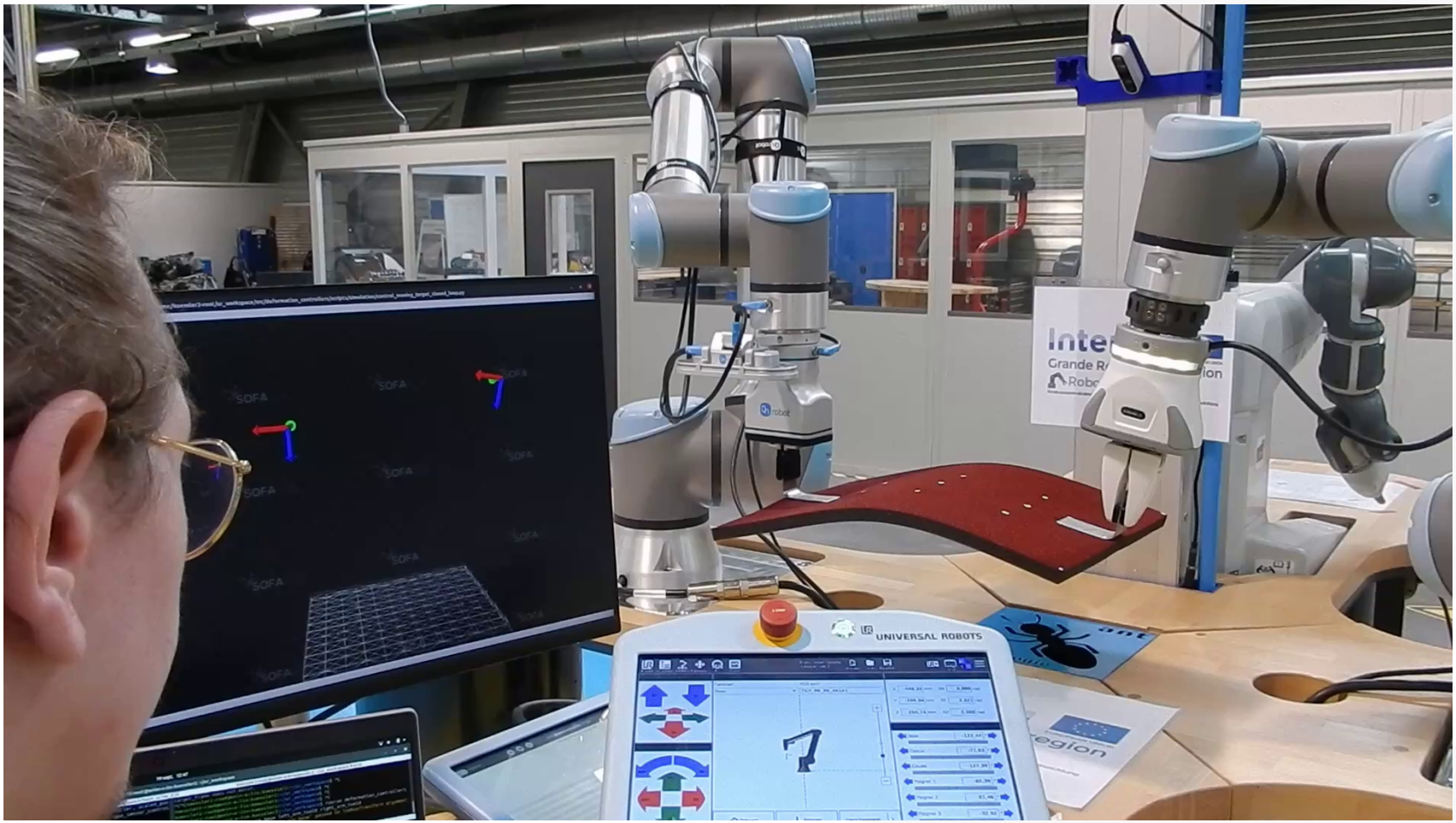


Experimental analysis



- Delay/following error between leader and follower
- Convergence despite model mismatch with shape error < 10 mm
- Steady FPS for simulation (around 15 Hz)

Online experiment - User-controlled master



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Conclusion and perspectives

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- Successful hardware and software implementation
- Quality of Jacobian estimation
- Robustness of the control scheme

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- Precision evaluation $\rightarrow$ address vision system limitations
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Future directions:

- Multi-robot manipulation ($n \geq 2$)
- Teleoperation in surgical context
- Human-object-robot manipulation

Thank you for your attention!

RoMaDO-SI@

KYOTO 2022 IROS iros2022.org

3rd workshop on RObotic MAnipulation of Deformable Objects: challenges in perception, planning and control for Soft Interaction (ROMADO-SI)

October 23rd, 2022 Kyoto, Japan

https://romado-workshop.github.io/ROMADO2022/

- Cosimo Della Santina, Delft University of Technology, Netherlands, and German Aerospace Center (DLR), Germany
  "to be defined"
- Fanny Ficuciello, Università di Napoli Federico II, Italy
  "Prostate biopsy using a soft/rigid robot"
- Yiannis Karayiannidis, LTH, Lund University, Sweden
  "Manipulation of Deformable Linear Objects: From simulation to real world experiments"
- Jeannette Bohg, Stanford University, USA
  "Real2sim for Deformable Objects"
- Xiang Li, Tsinghua University, China
  "Global Model Learning for Large Deformation Control of Elastic Deformable Linear Objects: An Efficient and Adaptive Approach"
- Doganay Sirintuna, Istituto Italiano di Tecnologia, Italy
  "Human-Robot Collaborative Carrying of Deformable Objects"
- Daniele Meli, University of Verona, Italy
  "Soft tissue manipulation in robotic surgery"
- Miguel Aranda, Universidad de Zaragoza, Spain
  "Shape control tasks in deformable object manipulation"
- Adrien Escande, Japanese-French Joint Robotic Laboratory (JRL), Tsukuba, Japan
  "to be defined"